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Spatial metrics from LiDAR roof mapping for fire spread risk assessment of informal settlements in Cape Town, South Africa.

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Abstract:

The risk of fire spread in informal settlements is significant and can be analysed as a function of the spatial arrangement of dwellings. Spatial metrics representing density and shape of dwellings are proposed as a method to identify settlements at high risk of fire spread. LiDAR data is used to map dwelling roofs for informal settlements in the City of Cape Town, South Africa. The LiDAR roof dataset is validated against a visually interpreted dataset digitized from 6 cm resolution aerial photography and is found to have an overall completeness and correctness accuracy of greater than 75% with systematic underrepresentation of roofs in the LiDAR dataset. Correlation analysis of metrics derived from the LiDAR dataset and the reference dataset indicates that only the edge density and landscape density metrics could be applied with confidence to all the settlements. These two metrics are then applied to the informal settlements of Kosovo and Imizamo Yethu. A high landscape density in combination with a low edge density is found to be indicative of fire spread risk. This study represents a first step in the development of spatial metrics for understanding informal settlement fire spread risk.

Keywords: Spatial metrics, LiDAR, informal settlements, fire spread risk, Geographic Information Systems, landscape density, edge density.

1. Introduction

Informal settlements (also sometimes referred to as slums, favelas, shanty towns) are at a significant risk of frequent and large fires affecting thousands of homes and people [1]. These fires have not been well studied in the past and thus little quantitative data on the controlling mechanisms and fire spread, and hence the characteristics of the settlement which control these, are available. Informal settlements are by their very nature unplanned and are not constructed with fire prevention in mind. Each dwelling unit can potentially be conceptualised as a discrete fuel package with a range of properties relating to ignition and fire intensity.

The potential risk of an informal settlement to fire spread can only be properly assessed if the size and distribution of individual dwellings are known, together with information on the fuel load. Fire spread between dwellings is a complex process and will depend on the geometry and characteristics of the dwellings and the settlement organisation. For a large fire where the length-scale of the fire is greater than the characteristic length-scale of the dwelling, then the dwellings can be considered as individual fuel packages which are heterogeneous in size and distribution.

The fire spread mechanism between dwellings has not yet been fully articulated however, flame radiation, direct flame impingement and fire brands are all considered to be likely. From these mechanisms it is clear that information on the density, gaps and connectivity of the fuel packages, together with general spatial heterogeneity, will be important metrics for determining risk of fire spread. Applying a methodology of assessing the size and distribution of dwellings, requires quantification of the spatial metrics of the dwelling arrangements to assess how the fire will develop beyond the dwelling of origin. Thus metrics which consider size of dwellings and gaps / nearest neighbours should be considered and thus geographic datasets of dwellings as individual/discrete objects are required. Object level geographic information of informal settlements is difficult to obtain as the high density of structures, overlapping of roofs and heterogeneous composition restrict automatic spatial separation of individual structures and approaches tend to be limited to visual interpretation [4]. In a review, Hofmann et al. [5] state that although object based image analysis (OBIA) techniques are suited to object extraction for informal settlement mapping, the variance of performance is large. On the other hand, although labour intensive, visual interpretation is still favoured by some and produces reliable results [5]. In this paper, the objects of interest are individual dwellings.

The City of Cape Town systematically captures Very High Resolution (VHR) (6 – 8 cm) aerial photography annually and makes this available online via a map server [6]. With this VHR photography freely available, a reference dataset can be captured through visual interpretation, against which subsequent mapping techniques at object level can be assessed. The City of Cape Town also has a LiDAR capture programme carried out at a 4-year interval. Two LiDAR capture missions have been carried out since inception in 2012 with the most recent taking place in 2016. The range in object based image analysis mapping accuracies, together with the availability of LiDAR data, open up the opportunity to assess the suitability of LiDAR for mapping individual dwellings in the City of Cape Town informal settlements. The accuracy of LiDAR mapped dwelling footprints in informal settlements can be assessed against a reference dataset digitised through visual interpretation of the VHR aerial photography by considering the method of area overlap and the quality of data completeness [7]. Furthermore, since the purpose of mapping the dwellings is to ascertain their location and distribution which in turn will enable understanding the fire spread risk of a settlement, the accuracy of LiDAR derived spatial metrics can be assessed against the spatial metrics derived from the reference dataset.

Spatial metrics vary in the kind of patterns they are suited to detect, and broad, often overlapping, metrics can be used to describe patterns found within a landscape [8] and can potentially quantify complex and interrelated spatial patterns into one or two variables and detect patterns of change [9]. Object based spatial metrics will be research objective specific, selected based on their value to quantify the specific landscape characteristic under study [10]. Therefore spatial metrics employed for fire spread risk assessment must represent the mechanisms of fire spread in informal settlements and an understanding of fire dynamics in informal settlements is essential to achieve this goal. These spatial metrics could then be used as a mechanism to inform potential changes to the structure of the settlement (i.e re-blocking to increase road widths to act as fire breaks and access routes for fire services) to mitigate the spatial aspects of fire spread risk. This would obviously have to be conducted in a co-developed way through local community stakeholders and municipalities to ensure that the plans were implemented effectively and sensitively to the local inhabitants wants and needs, as well as the requirements of other service providers (i.e. fire service, water companies etc.). The spatial metrics findings in this paper could therefore be used as part of that co-development and other aspects such as energy use and supply, construction materials, open spaces etc. should also be involved in such discussions.

The aim of this paper is thus fourfold: (1) To propose spatial metrics useful for determining fire spread risk in informal settlements; (2) To assess the completeness and correctness of a LiDAR dataset of dwellings mapped in Cape Town informal, (3) To determine the suitability of the LiDAR derived dwelling dataset for the proposed spatial metrics; and finally (4) By way of discussion to apply the spatial metrics to the settlements of Kosovo and Imizamo Yethu, two settlements with a known history of fire.

2. Study area

Situated in the south-western corner of South Africa (Fig. 1) and home to over four million people, the city of Cape Town is South Africa's second most populous city after Johannesburg and Africa's tenth most populous city [11]. Housing in informal settlements does not mimic the formal environment as by their very nature, there are no official state approved plans for these settlements. As a result, construction of dwellings is driven by available space and the cost of material, often resulting in dwellings constructed from cheap or recycled building materials. Due to competition for space, homes can be built very close together with little or only very narrow access paths. Some settlements are less densely constructed but these tend to be the newer settlements located further away from the city and places where there is little economic opportunity. Imizamo Yethu and Kosovo are both settlements with a history of extensive fires and are described in Gibson et al. [12]. Kosovo has experienced at least five fires impacting more than 12 dwellings since September 2016. Imizamo Yethu experienced a very large fire on 17 March 2017, described by Kahanji et al [13] which killed four people and displaced nearly 10 000.

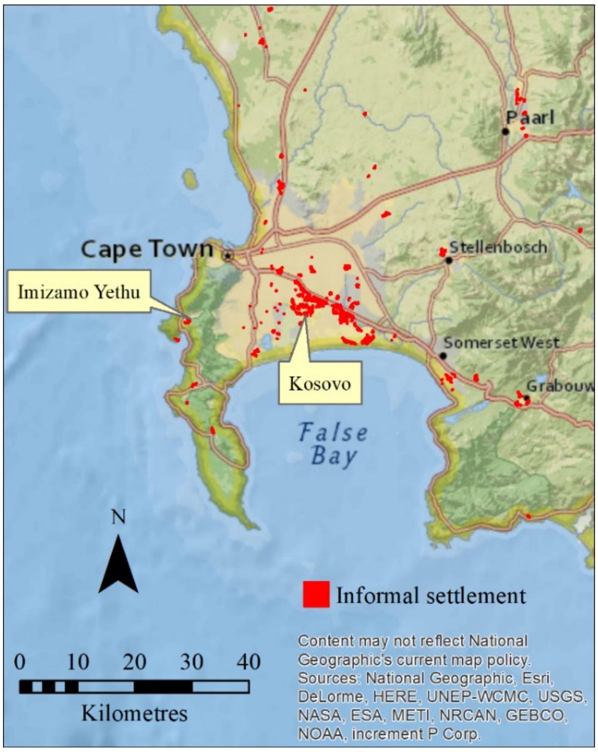


Fig.1. City of Cape Town extent showing distribution of informal settlements and location of Imizamo Yethu and Kosovo.

3. Material and Methods

3.1. Proposed spatial metrics

Spatial metrics in this context can be broadly divided into three categories. First, metrics indicating density or proximity of structures, secondly, metrics which represent the shape of structures and thirdly those representing the size (area) of structures. A variety of metrics can describe each of these categories but in the interests of space, only two metrics for each category will tested in this paper. However, the metrics representing the size of structures are not considered due to inadequacies in the reference dataset.

3.1.1. Dwelling density/proximity

Dwelling density, proximity and overcrowding are thought to be the controlling factors for conditions of fire spread in informal settlements [14], [15], [16]. Although litter and vegetation between dwellings and fuel stored outside dwellings can exacerbate fire spread, the largest fuel load within a typical settlement is found in the contents of dwellings and in the construction materials of dwellings themselves. It stands to reason that settlements with a high dwelling density will likely have a higher fuel load per unit area (although the relationship may not be linear) and dependent on the spatial arrangement of the fuel load, a higher risk for fire spread between dwellings. Spatial metrics capturing this characteristic of informal settlement layout should therefore be an indication of fire spread risk.

Dwelling density can be assessed in two ways (Fig. 2): as landscape density (PLAND) defined as the landscape covered by dwellings (m^2) divided by total landscape area (m^2), expressed as a percentage; or as patch density (PD) defined as the number of dwellings per unit area converted to number of dwellings per hectare. The landscape area (for PLAND) will be study dependent as it may be of interest to understand density at settlement scale, block scale or small neighbourhood scale. If households are individually captured, where one polygon equates to a single dwelling, then PD on its own may be a useful metric. However where the close proximity of dwellings to each other results in multiple dwellings being captured as a single polygon, the usefulness of this metric on its own is limited.

a) Landscape area (PLAND) equals sum of area of all dwelling footprints divided by the settlement area as percentage
Example = 901/1589*100 = 56.7%

b) Patch density (PD) equals count of dwellings divided by settlement area converted to count per hectare.
Example = 27/1589 * 10000 = 170 dwellings / ha

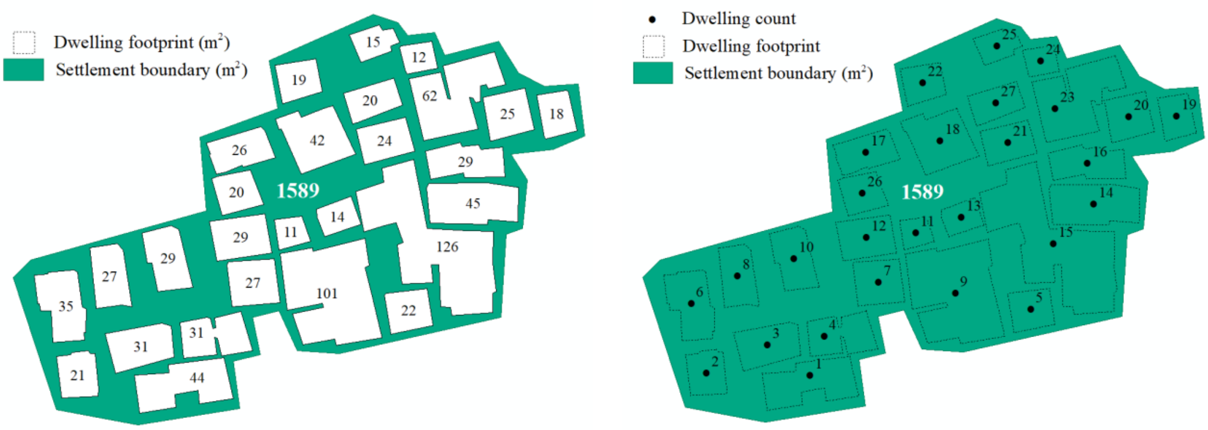


Fig. 2. Illustration of a) PLAND where the sum of the area of all dwellings (individual dwelling area (m^2) labeled) equals 901 m^2 and the settlement area is 1589 m^2, and b) PD where the number of dwellings equals 27 and the settlement area equals 1589 m^2, spatial metrics using a hypothetical settlement.

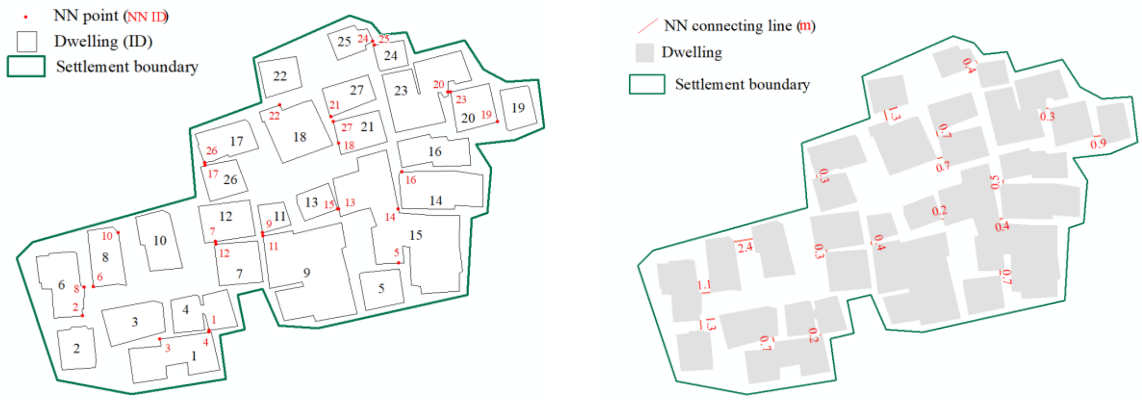
Landscape density (PLAND) in isolation indicates the total area occupied by dwellings but if considered in combination with Patch density (PD), further insights into the settlement layout may be deduced. For example, if two settlements (A & B) with high PLAND are compared, and one settlement (A) has high PD and the other (B) a low PD, it may be deduced that either A is comprised of individual dwellings which are smaller than those found in B, or dwellings in B are built in close proximity to each other and multiple dwellings have been mapped with a single polygon. Thus examining PD and PLAND in combination can offer further insights into the spatial characteristics of settlements than by would be obtained by considering the individual metrics in isolation.

Dwellings are often built in very close proximity to each other with separation between them on the order of centimetres. There is little, if any, adherence to building codes and walls are often built from, or lined with, combustible material. Dwellings in close proximity to the dwelling of origin therefore ignite quickly through direct flame impingement or flame radiation and it can be assumed that the adjacent dwelling will be ignited if the projected flame length is greater than the distance between dwellings [17]. As a result, settlements in which dwellings are closely bordered by other dwellings will be at higher risk of fire spread than settlements with larger separation distances between dwellings.

Euclidian mean nearest neighbour distance (ENN_MN) is the sum of the shortest Euclidean distance between a dwelling and its nearest neighbour for all dwellings in an area of interest divided by the number of dwellings in the area of interest with the measured distance based on shortest edge-to-edge distance (Fig. 3). This spatial metric should be considered together with Euclidian nearest neighbour distance standard deviation (ENN_SD).

a) Point on dwelling footprint at which it is closest to its nearest neighbour
Euclidian mean nearest neighbour distance (ENN_MN) equals the sum of all distances* divided by number of dwellings.

b) Lines connecting dwellings at their closest point with nearest neighbour (NN) distance.
Example ENN_MN = 16.7/27 = 0.62m



*Note that if two dwellings are each other's nearest neighbours, the distance between them is included twice. This is to ensure that the number of distances equals the number of dwellings.

Fig. 3. Illustration of Euclidean mean nearest neighbour distance (ENN_MN) using a hypothetical settlement as example a) dwellings showing the points at which each dwelling is closest to its nearest neighbour (labels in black are the dwelling ID, labels in red are the dwelling ID of the nearest neighbour. and b) Nearest neighbour (NN) vectors illustrating direction and magnitude with the location of the NN distance displayed as the NN connecting line and the length of the line labelled in red.

These two metrics analysed together can give an indication of both how far away from each other dwellings are located on average but also the variance in proximity. Thus a low Euclidean mean nearest neighbour (ENN_MN) with a low Euclidian nearest neighbour distance standard deviation (ENN_SD) may indicate a settlement at high risk of fire spread but a settlement with low ENN_MN with a higher ENN_SD may indicate portions of the settlement are at high risk but other portions may not be particularly risky. Since the nature of the nearest distance relationship can vary from for example, corner to edge, edge to edge (with or without openings), or corner to corner, each with differing fire spread characteristics, the use of the nearest neighbour is not considered further in this this paper. Furthermore, the ENN_MN as a vector (direction included) may offer more insights into fire spread risk, particularly if this is considered together with the wind direction during a fire event. Thus Landscape density (PLAND) and Patch density (PD) are used to represent dwelling density/proximity in this paper.

3.1.2. Dwelling shape

Once a dwelling is alight, the openings of the dwelling (which generally feature little, if any, internal compartmentation) will dictate the heat release rate of the fire and the fuel load will influence the duration of the fire. Typical fuel loads for an informal settlement dwelling are estimated at 321 MJ.m^{-2} [15]. The risk of spread arises from the boundary (or perimeter) of a dwelling where flames are ejected from windows, doors, gaps in wall panels, radiation from the dwelling walls and on the potential collapse of the dwelling. The risk of fire spreading both from and to a particular dwelling is thus a function of the perimeter and the fractal dimension (perimeter area relationship) of a dwelling.

Edge density (ED) and Fractal dimensions (FD) are spatial metrics which could help assess dwelling shape as an indicator of fire spread risk (Fig. 4). ED sums of the lengths (m) of all edge segments of dwellings in a settlement divided by the total area of an informal settlement (m^2), multiplied by 10000 (to convert to hectares) whereas FD considers the relationship of perimeter to area by dividing the sum of all edges by the sum of all roof areas in a settlement. Thus ED does not describe the shape of individual dwellings but rather provides an indication of the planes on to or from which fire can spread. On the other hand FD can be seen as a metric indicating the combination of fuel load (if related to area) and spread mechanism (via an edge).

a) Edge density (ED) = sum of all dwelling perimeters divided by the settlement area
Example = 668.2/1589 * 10000 = 4205 m/m^2

b) Fractal dimension (FD) = ratio of sum of dwelling perimeters to sum of dwelling areas
Example = 668.2/901.6 = 0.74

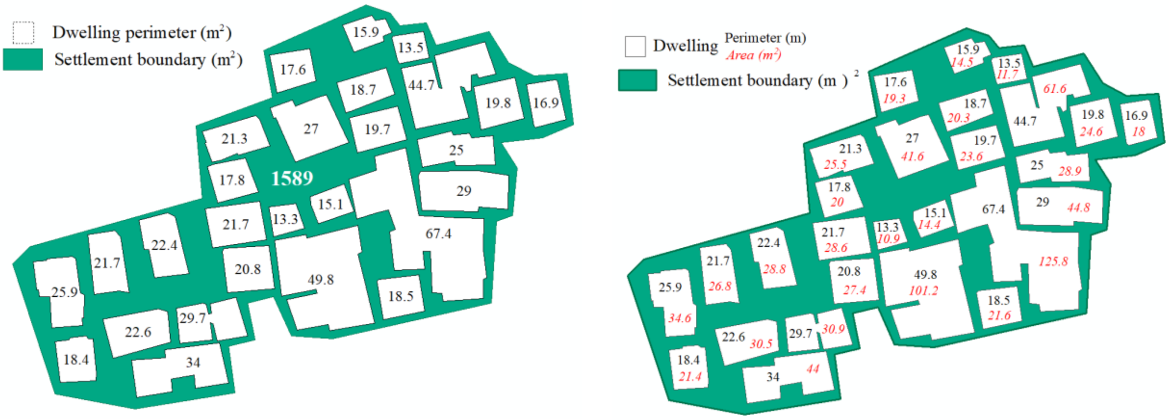


Fig. 4. Illustration using a hypothetical settlement to demonstrate the calculation of a) Edge density (ED) where 668.2 is the sum of all dwelling perimeters in the settlement area

(perimeter of individual dwellings labeled in black) and b) Fractal dimension (FD) where 668.2 is the sum of all dwelling perimeters in the settlement areas and 901.6 is the sum of all dwelling areas (labelled in red) in the settlement area.

3.2. LiDAR roof mapping

The remote sensing of informal settlements has been reviewed most notably by Kuffer et al. and Mahabir et al. [5,18]. When mapping objects in these environments the reported accuracy is highly variable [5] with the segmentation process remaining a challenge with few automated methods being reported [18]. This study takes a different approach in that the complementary advantages of integrating Light Detection and Ranging (LiDAR) data with very high resolution (VHR) aerial imagery provides a useful strategy to extract building roof outlines [19]. LiDAR provides a measure of the distance from the sensor (in this case on an aerial platform) to a target by illuminating the target with laser light and measuring the reflected return. The VHR aerial imagery provides spectral information to help separate trees from dwellings, while the LiDAR data provides elevation information to differentiate low lying objects from potential dwellings. A strategy termed 'classification by elimination' is adopted in a semi-automatic object based image analysis (OBIA), where objects of non-interest are classified as soon as detected, leaving the desired object (dwellings) as the last object to be classified. A workflow diagram of the dwelling roof extraction is shown in Fig. 5.

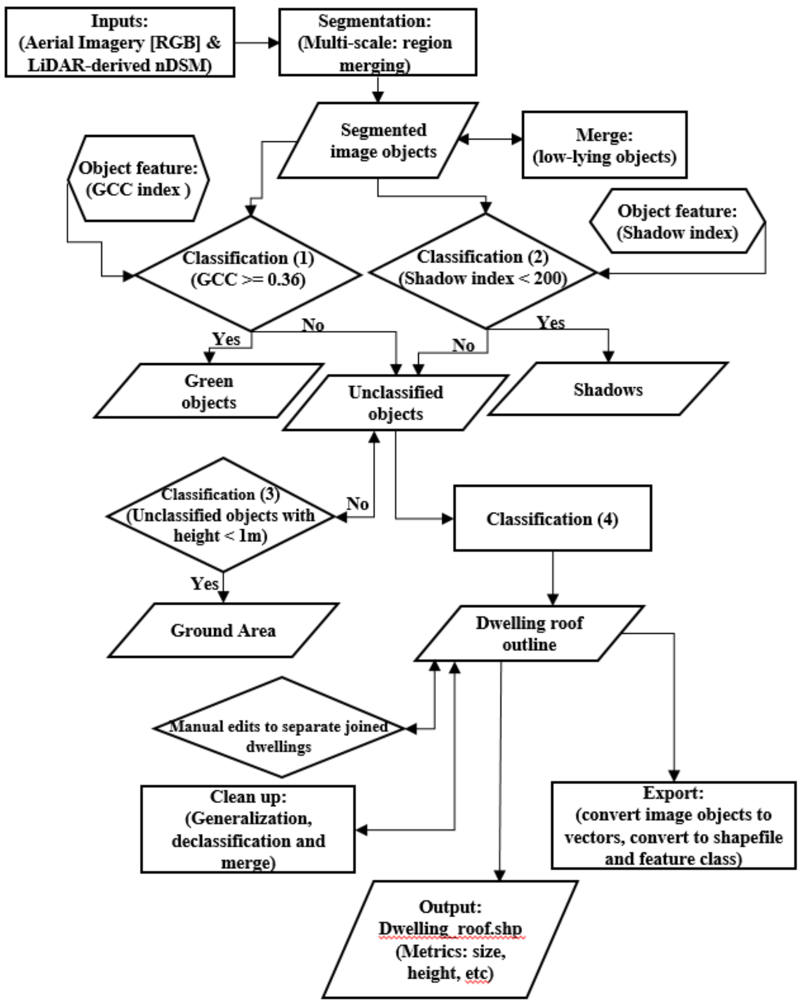


Fig. 5. Workflow diagram for extraction of dwelling roof outlines.

The segmentation process forms the basic foundation for any OBIA. Therefore, a multi-scale segmentation technique based on region merging is carried out, with the VHR imagery bands assigned equal weights in the segmentation process [20]. Using the elevation information from the LiDAR data and a height threshold of 1m, all low-lying objects are merged to clean-up the segmentation result.

The Green Chromatic Coordinate (GCC) index is then created to detect and classify the trees. The GCC index is calculated by dividing the green band of the VHR imagery with the mean of all the three bands (G / (R + G + B)) [21], where R is red, G is green and B is blue. A similar approach is used to detect and classify the shadowed area, by creating a shadow index. Subsequently, the low-lying objects already detected and merged are classified as ground areas. With the ground areas, shadows, vegetation and trees successfully detected and classified, the remaining image objects are the dwelling roofs.

The last step in the dwelling roof extraction process involves classifying the roof objects, cleaning up the dwelling roof classification, converting the roof image object to vector polygons and exporting it in a shapefile format for use in the spatial metric analysis.

3.2.1 Validation techniques

The study area for this research is informal settlements made up of 55 discontiguous polygons spread across the City of Cape Town covering a total area of 889 hectares. It is known that there can be large variation (building material, size of dwellings, typical dwelling design and density) both between and within informal settlements so any validation method would need to ensure that the subset validated is representative of the cross-section of variation. A stratified (on the basis of the polygon area) random sampling approach was used to select 185 points of interest thus larger polygons contain more points of interest and small polygons fewer. Points were buffered by 15 m to create circular areas of interest (AOI) of 707 m^2.

Within each area of interest (AOI), roofs of dwellings were manually digitised by an experienced operator from 6 cm resolution aerial photography captured in December 2013. The polygons were mapped at a scale of 1:200 and where the distance between roof sheets resulted in ambiguity with respect to the number of dwellings beneath the roof, the roofs were mapped as a single polygon. From a fire spread perspective, wall separation on the order of centimetres is short enough to allow flame impingement and therefore will not prevent fire spread and thus the decision was taken to map roofs beneath which the number of dwellings was ambiguous as a single polygon. The manually digitised visually interpreted ArcGIS polygon shapefile serves as the reference dataset against which the LiDAR mapped roofs are validated.

Two separate techniques are used to assess the accuracy of the LiDAR roof dataset: (1) a completeness and correctness analysis and (2) a measure of the area of overlap between the two datasets.

The completeness of the dataset (also known as the Producer's Accuracy) is the percentage of entities in the reference which were detected whereas the correctness (User's Accuracy) provides an indication of how well the detected entities match the reference [22]. The use of the Producer's and User's Accuracies are designed around pixel or point based validation. From the 185 areas of interest (AOI), 1 point per AOI was randomly assigned to a dwelling polygon and 1 point per AOI to the background (non-dwelling). 19 AOI's do not contain any dwelling polygons in the reference dataset and therefore a total of 166 dwelling points were created for validation along with 185 background points. True positives (dwelling in LiDAR roof dataset, dwelling in reference), false positives (dwelling in LiDAR roof dataset, background in reference), true negatives (background in both LiDAR roof dataset and reference), false negatives (background in LiDAR roof dataset, dwelling in reference) are used to determine the Producers and User's Accuracies and are evaluated in an error matrix to assess the overall accuracy of the dataset against the reference. Readers are referred to [23] for explanations of these concepts.

An alternative validation technique when considering polygons, is the method of area of overlap to establish the quality of a buildings footprint against a reference [24]. In this method, the two polygon layers are overlaid and true positives, false positives and false negatives are assessed with respect to proportion of area. A true positive result is the area of overlap between the two layers, where dwellings are mapped in both the LiDAR roof dataset and the reference. A false positive, or extra-lap, is where an area is wrongly detected as a dwelling in the LiDAR roof dataset and underlap is a false negative (dwelling in LiDAR roof dataset but background in reference).

As per the presence and absence validation, the area of overlap measure is applied to all 185 AOIs to assess common and exclusive areas.

3.3. LiDAR metric suitability

The spatial metrics for each AOI are calculated in ArcGIS using both the LiDAR roof dataset and the reference roof dataset. The accuracy of spatial metrics produced from the LiDAR dataset are validated using correlation statistics to determine which metrics may be reliably applied to the settlements of Kosovo and Imizamo Yethu to ascertain their use in real fire prone environments.

4. Results

4.1. LiDAR roof dataset validation

The LiDAR roof dataset comprises of 62 205 individual polygons across all settlements. Once clipped to the area of interest (AOI), it contains total of 1340 compared with 1433 polygons in the reference dataset. The completeness and correctness of the LiDAR roof dataset is assessed against the reference dataset and the results are shown in a confusion matrix (Table 1). The Kappa Coefficient is a widely used measure of the accuracy of thematic maps produced from remotely sensed images however it is widely misused since the requirement of the independence of samples is often not met [25]. Since the "no roof" class in this research is simply the omission of a roof being mapped, the requirement of independence has not been met and although a Kappa Coefficient of 0.52 is reported (indicating neither poor nor good agreement), it should not be the only measure of accuracy. The confusion matrix (Table 1) reveals that the Users accuracy of roofs (85.0%) is higher than the Producers accuracy of roofs (61.5%) with an overall accuracy of 76.6%. Therefore although many roofs in the reference dataset are omitted from the LiDAR roof dataset (Producers accuracy of 61.5%), the likelihood of a roof being incorrectly mapped in the LiDAR dataset is low (Users accuracy 85.0%). This implies that the LiDAR roof dataset systematically underrepresents the coverage of roofs in the AOIs.

Table 1. Accuracy assessment of completeness and correctness of the LiDAR roof dataset against the reference dataset.

		Reference			
		No roof	**Roof**	**Total**	**Users Accuracy**
LiDAR roof dataset	**No roof**	166	64	230	72.2%
	Roof	18	102	120	85.0%
	Total	184*	166	350	
	Producers accuracy	90.2%	61.5%	**Kappa coefficient**	0.52

*One AOI which had roofs mapped in the reference set had no roofs mapped in the LiDAR set reducing the number of points to 184.

The reference dataset contains a total of 42 582 m^2 of roofs as opposed to the 33 825 m^2 of roofs contained in the LiDAR roof dataset (Table 2) with the LiDAR roof dataset thus underrepresenting roofs by 20.6%. This figure does not however provide the measure of overlap in the footprints of both datasets. True positives cover 27 894 m^2 of a possible 42 582 m^2 representing a 65.5% overlap of footprints from both datasets. False negatives or underlaps where roofs in the reference dataset are not mapped as roofs in the LiDAR roof dataset comprise 14 688 m^2 (34.5%) of all roofs in the reference dataset. False positives or extra-laps where roofs are incorrectly mapped in the LiDAR roof dataset, comprised 5 931 m^2 out of a possible 33 825 m^2 (17.6%).

Table 2. Accuracy assessment using measure of area of overlap technique.

		Reference		**Total (m^2)**
		No roof (m^2)	**Roof (m^2)**	
LiDAR roof dataset	**No roof (m^2)**	N/A	[$]14688	14688
	Roof (m^2)	[*]5931	[&]27894	33825
Total (m^2)		5931	42582	48513

[$]underlap, [&]overlap, [*]extra-lap.

This result confirms the completeness and correctness accuracy assessment as it indicates that although the LiDAR generally underestimates the total area covered by roofs (79.4% of total roofs in reference dataset), the LiDAR roof dataset is more likely to omit a roof (34.5% underlap, Producers accuracy 61.5%) than to incorrectly map a roof (17.5% extra-lap, Users accuracy 85.0%).

4.2. Spatial metric validation

The accuracy of spatial metrics produced from the LiDAR dataset are validated by calculating the metric for each area of interest (AOI) for both the LiDAR roof dataset and the reference dataset and basic statistics across all AOIs are shown in Table 3. Scatterplots (Fig. 6) of the four spatial metrics tested reveal the strongest agreement between the LiDAR roof dataset and the reference when the Landscape density (PLAND) metric is considered with the least agreement seen in the Fractal dimension (FD) spatial metric. The coefficient of determination (r^2) for each spatial metric are applied it is found that there is best correlation in the PLAND and Edge density (ED) spatial metrics (r^2 = 0.72 and 0.69 respectively) with weaker correlation observed in the Patch density (PD) and FD spatial metrics (r^2 = 0.40 and

0.12 respectively). It is likely that the outliers visible on the FD graph are contributing to the weak correlation here. These results imply that only the application of the PLAND and ED spatial metric should be applied to the entire LiDAR roof dataset as the confidence in accuracy of the other spatial metrics is low.

Table 3. Basic statistics Patch density (PD), Landscape density (PLAND), Edge density (ED) and Fractal dimension (FD) of LiDAR and reference roof datasets and their correlation and error statistics.

	PD* (dwellings per ha)	**PLAND (%)**	**ED (m/ha)**	**FD (no unit)**
Min LiDAR	0	0	0	0
Min Reference	0	0	0	0
Max LiDAR	25	67.5	6788	8.48
Max Reference	22	99.5	6719	3.85
Mean LiDAR	8.47	28.1	2770	1.17
Mean Reference	8.52	35.4	2728	0.83
Median LiDAR	7	28.4	2846	1.07
Median Reference	9	37.0	2800	0.80
r^2	0.40	0.72	0.69	0.12

*Unit of area is the area of the AOI (707 m^2).

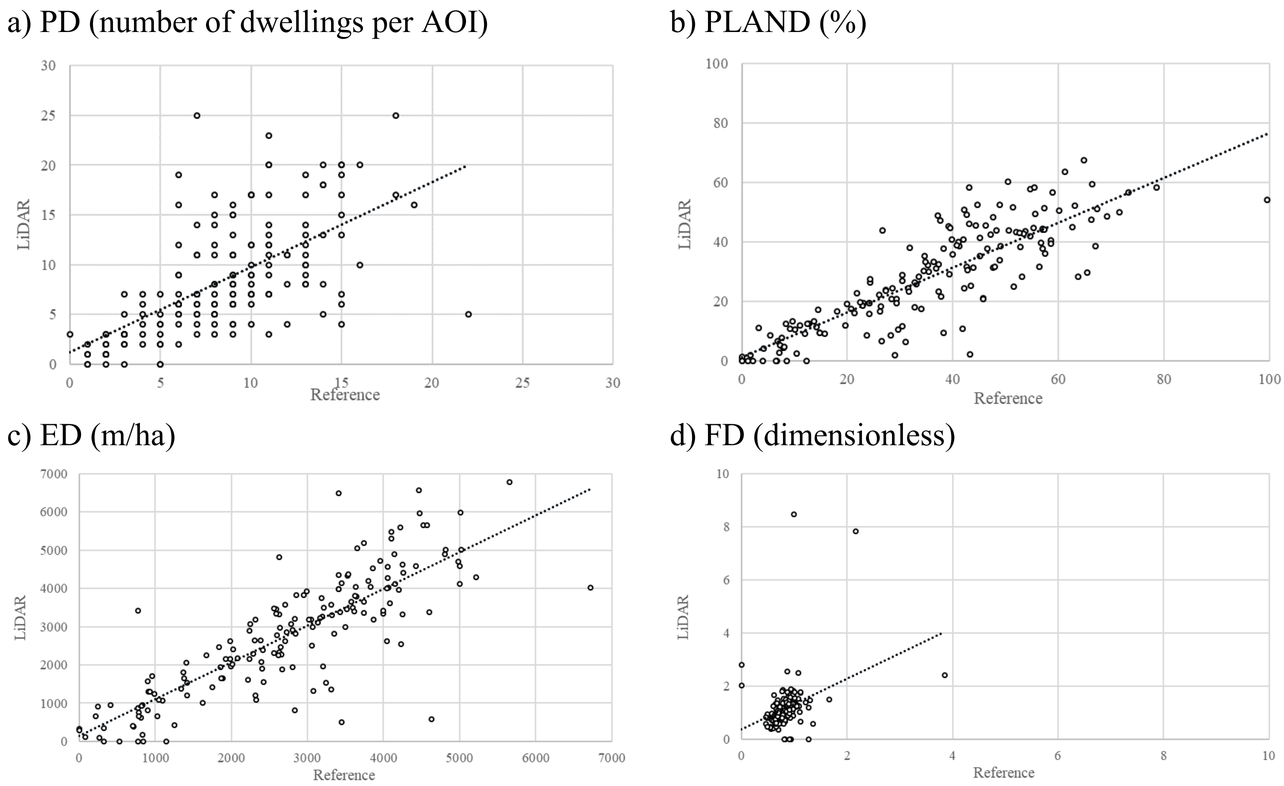
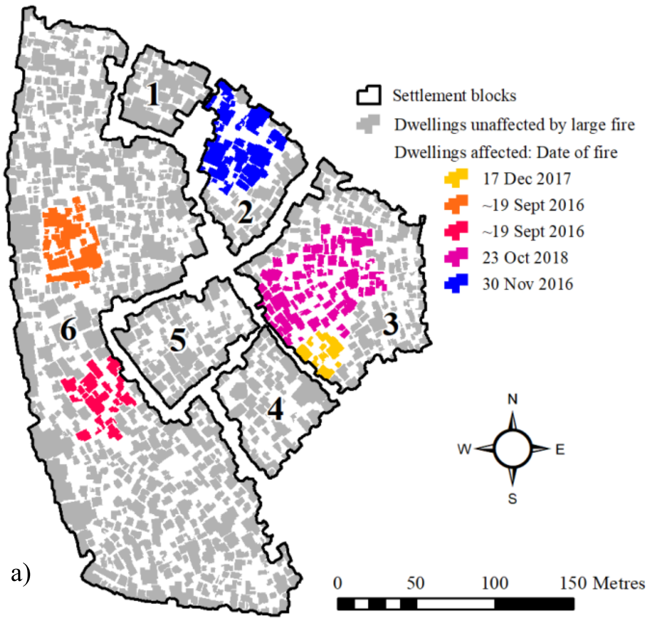


Fig. 6. Scatterplot of spatial metrics applied to LiDAR and reference roof datasets a) Patch density, PD (number of dwellings per AOI), b) Landscape density, PLAND (%), c) Edge density, ED, d) Fractional dimension (FD).

5. Discussion

Two spatial metrics derived from LIDAR mapping can be used reliably as they were validated against metrics derived from a reference dataset. These are Landscape density (PLAND) and Edge density (ED) and these metrics are now applied to the informal settlements of Kosovo and Imizamo Yethu (locations shown in Fig. 1). Kosovo has experienced at least five multi-dwelling fires since September 2016 (Fig. 7. a) and by dividing the settlement into clearly demarcated blocks, spatial metrics for the settlement blocks can be compared with metrics for those areas affected by fire. Since the effects of wind and the firefighting intervention are unknown, absolute conclusions can not be drawn however trends can be highlighted. It can be seen that when comparing the fire burn scar metrics to the block metrics, generally fires occur in areas with a high PLAND and a low ED. The high PLAND matches the expectation that fire will spread in areas with a high dwelling density however the low ED in area affectied by fire was contrary to expectations since it was postulated that fire will spread from the edge of a dwelling and thus the more edges in an area, the higher the likelihood of spread. This perhaps highlights the need to look at spatial metrics in combination rather than in isolation as another factor is contributing to spread which was not anticipated. For example, high PLAND with low ED may be indicative of large dwellings in close proximity to each other. From this observation, it appears that Block 1 is at high fire spread risk. It should be noted at this point that other environmental factors are known to have an impact on fire spread in informal settlements which are not discussed in this paper. For example topography, wind speed and wind direction [13] particularly when considered in relation these spatial metric will have an influencing factor on the fire risk of a particular settlement. This is not however considered in this paper and remains a topic of future research.



b) Settlement block metrics

Block number	PLAND	ED
1	73.3	6781
2	61.2	8541
3	52.5	10251
4	55.1	9558
5	54.6	10619
6	56.8	8270

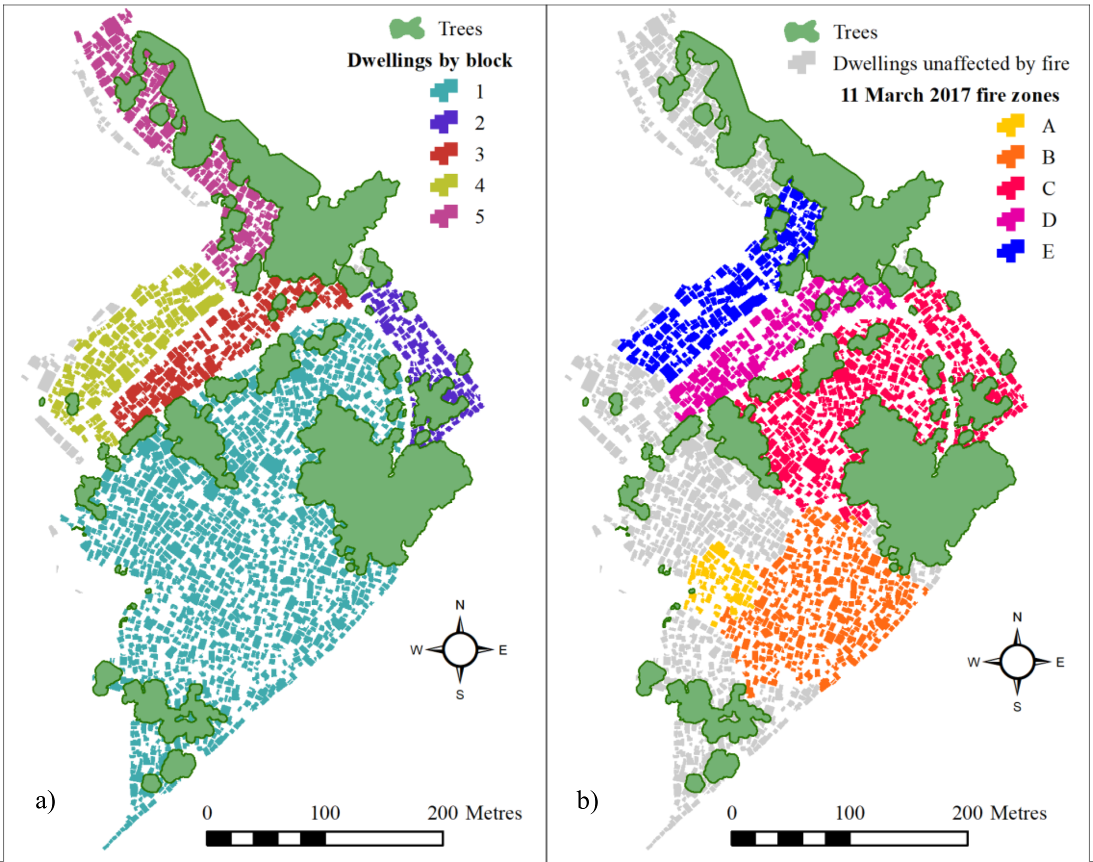
c) Fire burn scar metrics

Fire date	PLAND	ED
17 Dec 2017	64.8	6070
~19 Sept 2016 (N)	72.0	4784
~19 Sept 2016 (S)	66.4	6590
23 Oct 2018	57.1	5621
30 Nov 2016	68.0	5132

Fig. 7. a) Kosovo blocks and known fires since September 2016 with corresponding b) settlement block and c) fire burn scar Landscape density (PLAND) and Edge density (ED) metrics.

In the case of Imizamo Yethu, settlement blocks (Fig. 8. a) and the fire of 17 March 2017 (Fig. 8. b) are considered. Kahanji et al [13] divided the area affected by the fire of 17 March 2017 into fire zones and calculated both the linear and area rate of spread for each zones based on the observations of fire fighters at the scene. Kahanji et al [13] noted that Zones B and C are complicated by the high vegetation cover and the steep slope at this particular part of the settlement and therefore these zones are excluded from the spatial metrics assessment.

By examining the settlement Block metrics with the results of the Kosovo metrics in mind (high Landscape density (PLAND), low Edge density (ED) representing higher risk of spread), it can be seen that settlement Blocks 3 and 4 should represent the highest risk. These blocks roughly correspond with fire Zones D & E where according to Kahanji et al [13], the fire was spreading at a linear rate of 55 m/hr and growing in area at a rate of 8300 and 6200 m^2/hr for Zones D & E respectively. By comparison, Zone A had both a lower PLAND and a higher ED than Zones D and E and it had a reported fire spread rate of 30 m/hr (linear) and increased in size at 2000 m^2/hr. This implies that PLAND and ED together may be indicative of risk however this would need to be tested on other settlements which have experienced multi-dwelling fires.



c) Settlement block metrics			d) Fire zone metrics		
Block no	**PLAND**	**ED**	**Zone**	**PLAND**	**ED**
1	52.6	5558	A	62.9	7125
2	58.7	6970	B	49.6	5669
3	64.5	6092	C	56.5	6579
4	63.6	5792	D	64.9	6636
5	67.7	6822	E	64.8	6490

Fig. 8. Imizamo Yethu a) divided in blocks, b) showing fire zones of fire on 17 March 2017, c) settlement block and d) fire zone Landscape density (PLAND) and Edge density (ED) metrics.

Kahanji et al. [13] discuss the influence of the wind on the Imizamo Yethu fire as the wind initially blew upslope in Zone A. It thereafter changed direction and blew downslope in Zones B – C. Interesting future work could analyse the direction and magnitude of nearest neighbour vectors together with directional environmental factors such as aspect and wind to determine if spatial metrics contribute to more dangerous fire spread conditions under certain environmental conditions.

6. Conclusions

Informal settlements in Cape Town have a history of multi-dwelling destructive fires and research into the fire spread mechanism and impacts on the rate of spread have been limited to date. Individual dwellings may be conceptualized as individual fuel packages and thus the spatial arrangement of these dwellings can help identify areas at high risk of multi-dwelling fires. However obtaining geospatial datasets of individual dwellings can be time consuming and expensive. In this paper the accuracy of a LiDAR derived dwelling dataset of informal settlements in the City of Cape Town is validated against a reference dataset digitized from high resolution aerial photography. Good agreement is found between the two datasets with an overall accuracy of 76.6%. Spatial metrics are proposed which represent dwelling density in the form of landscape density (PLAND) and dwelling density (PD). In addition spatial metrics representing dwelling shape are proposed as fractional dimension (FD) and edge density (ED). These metrics are calculated for both the LiDAR and the reference dataset and a correlation is found between the LiDAR and reference dataset derived PLAND and ED with r^2 of 0.72 and 0.69 respectively. These metrics are applied to the settlements of Kosovo and Imizamo Yethu in Cape Town, two settlements with a recent history of multi-dwelling fires. It is observed that areas which have experienced recent multi-dwelling and devastating fires generally have a relatively high PLAND in combination with a relatively low ED.

This paper has demonstrated a method to create object based datasets of dwellings for informal settlements using LiDAR data to a high level of overall accuracy. Furthermore, spatial metrics calculated from the LiDAR dataset, proposed to represent dwelling density and dwelling shape, correlate well the same metrics calculated using the reference dataset implying that LiDAR can be used for spatial metric mapping in informal settlements. As the volume of high resolution imagery continues to grow globally, it follows that methods of mapping objects (dwellings in this case) will continue to be developed. The findings on which spatial metrics are indicative of fire spread in one part of the world could be tested in other regions, particularly those which experience multi-dwelling fires frequently [26]. Research into spatial metrics and their relation to fire safety therefore has potential to expand and fire experiments to validate the spatial metric observations are essential to prove, as found in this research, high dwelling density and low edge density represent a high risk of fire spread in informal settlement environments. Finally, spatial metrics in isolation can only observe the exposure of these informal settlement homes to potential fire spread. It will be up to communities and authorities to use this information together to develop potential settlement changes in combination with other potential interventions.

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LiDAR data from which dwellings were extracted was kindly supplied by the City of Cape Town.

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Figure captions

Fig. 1. City of Cape Town extent showing distribution of informal settlements and location of Imizamo Yethu and Kosovo.

Fig. 2. Illustration of a) PLAND where the sum of the area of all dwellings (individual dwelling area (m^2) labeled) equals 901 m^2 and the settlement area is 1589 m^2, and b) PD where the number of dwellings equals 27 and the settlement area equals 1589 m^2, spatial metrics using a hypothetical settlement.

Fig. 3. Illustration of Euclidean mean nearest neighbour distance (ENN_MN) using a hypothetical settlement as example a) dwellings showing the points at which each dwelling is closest to its nearest neighbour (labels in black are the dwelling ID, labels in red are the dwelling ID of the nearest neighbour. and b) Nearest neighbour (NN) vectors illustrating direction and magnitude with the location of the NN distance displayed as the NN connecting line and the length of the line labelled in red..

Fig. 4. Fig. 4. Illustration using a hypothetical settlement to demonstrate the calculation of a) Edge density (ED) where 668.2 is the sum of all dwelling perimeters in the settlement area (perimeter of individual dwellings labeled in black) and b) Fractal dimension (FD) where 668.2 is the sum of all dwelling perimeters in the settlement areas and 901.6 is the sum of all dwelling areas (labelled in red) in the settlement area.

Fig. 5. Workflow diagram for extraction of dwelling roof outlines.

Fig. 6. Scatterplot of spatial metrics applied to LiDAR and reference roof datasets a) Patch density, PD (number of dwellings per AOI), b) Landscape density, PLAND (%), c) Edge density, ED, d) Fractional dimension (FD)..

Fig. 7. a) Kosovo blocks and known fires since September 2016 with corresponding b) settlement block and c) fire burn scar Landscape density (PLAND) and Edge density (ED) metrics.

Fig. 8. Imizamo Yethu a) divided in blocks, b) showing fire zones of fire on 17 March 2017, c) settlement block and d) fire zone Landscape density (PLAND) and Edge density (ED) metrics.

Highlights:

- Spatial metrics proposed for fire spread risk in informal settlements.
- LiDAR dataset used to map dwellings in informal settlement in Cape Town.
- LiDAR derived spatial metrics of landscape density and edge density reliable.
- High landscape density with low edge density may indicate high fire spread risk.